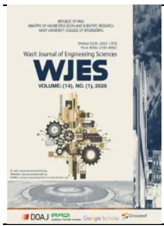

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Original Research

Design and Implementation of an Electroencephalography System for Emotion Recognition

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ABSTRACT

Emotions directly affect essential functions in human cognition, decision-making, and interactions. Any change in a person's emotions can lead to different patterns in brain wave signals. Electroencephalography (EEG) is one of the key methods used to measure the brain's electrical activity. Emotion identification through EEG data has become a crucial element of human-computer interaction. Recently, the increasing need for monitoring brain activity has been measured by EEG devices, and the high price of these devices, which are not accessible outside of the laboratory for personal use, has prompted the development of low-cost wearable EEG devices. This paper introduces the design and implementation of an EEG system using available and low-cost components. This EEG system applies to emotion identification using the STM32F103C8T6 microcontroller, two-stage amplifiers, and filtering by bandwidth of (0.5-48) Hz. These data are logged and processed using MATLAB 2024, where Power Spectral Density (PSD) is applied for feature extraction and then the Support Vector Machine (SVM) for emotion detection, such as boredom, calm, fear, and happiness. Results show that this system can achieve an accuracy of a range between (79-83) % for the four emotion classifications. This study concludes by summarizing the practical importance of Electroencephalography (EEG) signals in emotion recognition, focusing on its potential for future applications.

Keywords: Electroencephalography, Emotion recognition, STM32F103C8T6, Support vector machine.

1. Introduction

Human emotions are complex responses that encompass psychological and physiological aspects triggered by various external stimuli. The importance of emotion recognition is increasing in daily life and work. They are essentially utilized in psychology, artificial intelligence, medical treatment, computer vision, etc. [1].

Emotion recognition employing physiological signals demonstrates significant benefits in accuracy and functionality, including EEG signals, facial expressions, eye movement (EM), and electrocardiograms (ECG) [2]. Among different physiological signals, EEG signals are inherently spontaneous and can provide immediate information on brain activity. Consequently, the analysis of EEG signals is highly dependable and efficient in recognizing emotions [3].

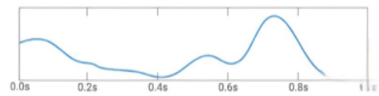
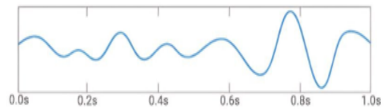
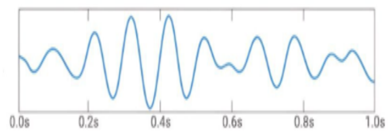
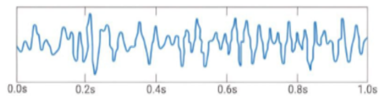
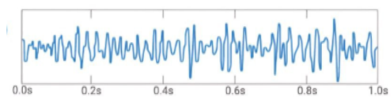
The EEG signal plays an essential role in detecting changes in emotional states. In an adult, EEG signals are collected from the brain waves through electrodes placed over the human scalp. The EEG signal is a non-stationary signal ranging from 5 µv to 100 µv with low frequency [4]. The EEG signals are categorized into five rhythmic bands, namely, delta (0.5-4) Hz, theta (4-8) Hz, alpha (8-13) Hz, beta (13-30) Hz, and gamma (>30) Hz, as illustrated in Table 1, which provides the properties of the bands [5].

EEG signals are a vital metric to measure human brain emotional activities. Still, such technologies are usually costly and demand specialized expertise; therefore, their use is often restricted to a few individuals. EEG devices have seen continuous improvements, most of which allow physicians to assess better how well they diagnose and predict cognitive disabilities, and many abnormal brain diseases [6].

In recent years, efforts have been made to make EEG devices affordable and accessible to the general market, facilitating increased commercial and personal data utilization. Emotion recognition systems utilize various applications, including human-computer interaction (HCI), emotional comprehension, brain-computer interfaces (BCI), and the medical field [7].

In the research field, emotion recognition generally includes emotion induction, EEG signal acquisition, EEG preprocessing, feature extraction, and emotion recognition, as illustrated in figure 1.

Table 1. Properties and Frequencies of Various Brain Waves [5].

Types	Brain Active	Functions	Shape of Band
Delta Waves (0.5-4) Hz	A delta wave occurs in the temporal and parietal lobes.	Deep sleep	
Theta Waves (4-8) Hz	Theta waves occur in the midline of the prefrontal lobes	Drowsiness, Deep meditation	
Alpha Waves (8-13) Hz	An alpha wave occurs in the The right occipital and the posterior parietal lobes.	Relaxed awareness; Eye closing	
Beta Waves (13-30) Hz	Betas wave occurs in the frontal lobe and the parietal lobe	Active Thinking, Attention, Behavior, settling problems	
Gamma Waves (> 30HZ)	Gamma waves occur in the left frontal lobe and the right temporal lobe	Sensory Processing, High-Level Information Processing, and Specific Cognitive Motor Function.	

A typical emotion detection based on an EEG system involves many steps: acquisition of EEG signals, preprocessing, feature extraction, and classification. Feature extraction is crucial in a system that directly affects the efficiency of the classification [5]. This paper aims to design and implement an EEG system for emotion detection. The research is based on an EEG acquisition data, amplification, filtering, an STM32 microcontroller, and a personal computer to log and process the signal.

In feature extraction and classification techniques for clarity, the ability to detect an emotional state from raw data appears. Thus, studying emotion based on EEG data is of very practical importance and demonstrates its suitability for various applications [6].

The unique contribution of this research lies in three aspects: the implementation of a low-cost EEG acquisition system based on STM32F103C8T6 microcontroller and cost-effective commercial components, integration of custom-designed amplification and filtering stages designed for emotion recognition, and implementation of a practical GUI MATLAB2024 that enables real-time monitoring, artificial removal, and saving the data for other times.

These contributions distinguish this study from existing high-priced EEG systems and focus on its potential for accessing the various applications.

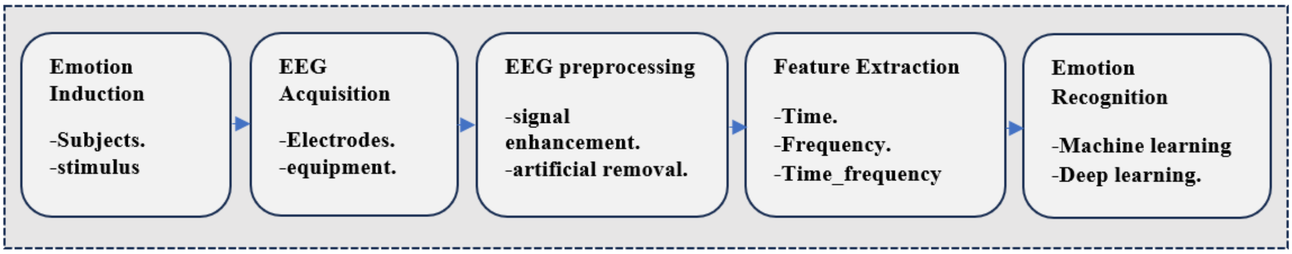


Figure 1. Schematic Diagram of Emotion Recognition [8].

2. Literature Reviews

Emotion recognition based on EEG signals introduces an important role in various medical and consumer applications. Currently, a wide variety of sources of data are included in emotion recognition, comprising EEG signals, facial expressions, and voice signals. It's fundamental to recognize that facial and voice signals can be intentionally hidden or processed, losing their authenticity in reverse EEG signals [2]. Electroencephalography (EEG) signals introduce a direct measure of brain activity connected to emotions; therefore, the primary sources of raw EEG data are used to detect emotional state and explore difficult brain mechanisms [6].

In recent years, increasing interest in emotion recognition employing EEG signals has become an important and thoroughly studied subject. Currently, this exceeds applications of human-computer interaction. It has been implemented in various applications such as mental health issues, depression, etc. [7]. Moreover, it has facilitated the development of systems for sentiment intelligence that use EEG signals and virtual reality experiences.

In Houssein et al. (2022) [9] the authors study a development prototype of detecting human emotional states based on the analysis of EEG signals. In practice, the authors have realized the possibility of classifying the human emotional states (valence, arousal, and dominance) via training a deep neural network CNN-1D. The traditional neural network's results are very good according to the current state of research. However, the high metrics realized refer to a small population sample. Finally, this prototype could be a suitable support tool in the medical field and large-scale studies.

Suhaimi et al. (2022) [7] aim to use a virtual reality (VR) technology to evoke four classes of emotions (happy, fear, relaxed, and disgust), to record brainwave activity utilizing a low-cost wearable EEG headset that is compact and small. Utilizing VR stimuli, the authors evaluate the emotion detection system by applying the popular support vector machine (SVM Class Weight Kernel), obtaining 85.02% detection accuracy.

Shilaskar et al. (2023) [10] focus on using EEG signals to detect emotion. Using video stimuli to induce six classes of emotions (happy, sad, fear, disgust, neutral, and motivation) for eight subjects. The authors emphasize 79.34% by utilizing the support vector machine (SVM) algorithm. This system could be a good aid in the medical field in assessing mental health issues.

Attia et al. (2024) [11] aim to utilize an SVM classifier to recognize emotion based on EEG signals. It highlights the effectiveness of EEG in detecting emotions compared to conventional techniques such as speech and facial expressions. This work achieves an overall accuracy of 92% with the support vector machine.

Mouazen et al. (2024) [12] extensively evaluate the effectiveness of support vector machine learning and deep learning in detecting emotional classes using a DEAP dataset. Using video stimuli to evoke emotions (arousal, valence, dominance, and liking). The hybrid algorithms achieved an accuracy of (85-94) %.

3. Materials and methods

The section describes the hardware and software components used in the proposed EEG system for emotion recognition, along with the methodology followed for data acquisition, processing, feature extraction, and classification.

3.1. Materials

3.1.1. Electrodes

EEG signals are usually collected through electrodes; biopotential electrodes move ionic physiological signals to the electrical signals that stay on the outer layer of the skin [13]. Regarding signal quality and user comfort, using dry electrodes with silver/silver chloride (Ag/Ag-Cl) is typically safer and is placed directly to the skin of the scalp without using gel, resulting in a higher impedance of the electrode. Conversely, more susceptibility to motion artifact [6].

The electrodes are affixed to a head cap and distributed based on the traditional (10-20) International system. As demonstrated in figure 2, the designations of the electrodes, FP, AF, F, FC, T, P, and O, correspond to frontopolar, anterior frontal, frontal, frontocentral, temporal, parietal, and occipital, respectively. The odd-numbered suffix denotes the left hemisphere, while the even-numbered suffix represents the right hemisphere.

EEG acquisition effectively records and analyzes brain waves in participants, offering the benefits of low cost and ease of wearability [14]. These technologies have been increasingly readily available in recent years [15], leading to a rise in the application domain, which involves both research and medical modes [16].

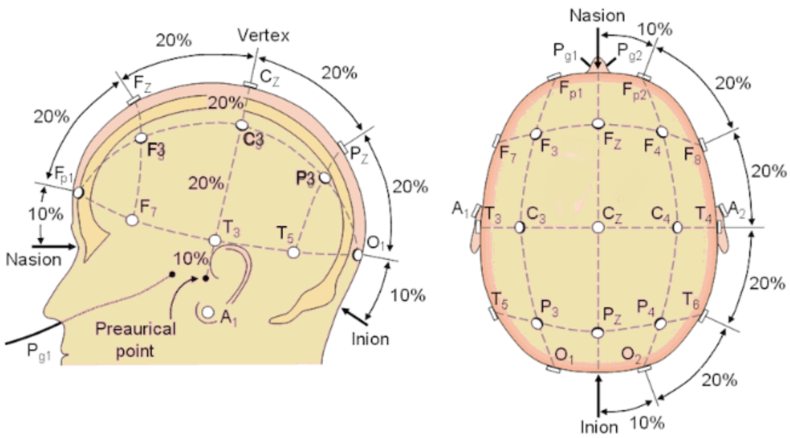


Figure 2. 10-20 The International System [17].

3.1.2. Instrument amplifier TL084

The TL084 operational amplifier, manufactured by companies such as Texas Instruments, is part of the TL08x series and is widely recognized for its high input impedance (10^{12} MΩ), which prevents signal attenuation due to impedance mismatch, while its low noise performance ensures that weak neural signals are accurately captured and amplified with minimal distortion [18]. Furthermore, its low power consumption and wide supply voltage range (±3V to ±18V) make it well-suited for biomedical devices.

The TL084 can be effectively incorporated into processing EEG front-end amplifier circuits, often serving as the initial gain stage before filtering and digitization. In EEG applications, the ability to amplify low-amplitude brain signals (typically in the microvolt range) without loading the signal source is vital.

3.1.3. Filters

Filters are fundamental components in signal processing systems, which are designed to selectively attenuate or enhance specific frequency components of a signal [19]. These circuits play a crucial role in eliminating unwanted noise and preserving signal integrity, particularly in applications dealing with low-amplitude and high-sensitivity measurements, such as electroencephalography (EEG) [20]. In this system, the primary amplifier circuit and the construction of low-pass and band-pass filters are implemented using active elements. In EEG systems, filters are essential for removing power-line interference (50 Hz), muscle artifacts, and other physiological noise.

3.1.4. 2nd stage amplifier

In multistage amplifier systems, particularly those designed for electroencephalography (EEG) signals, the second amplifier stage plays a crucial role in signal conditioning, noise suppression, and dynamic range optimization [21]. The second amplifier stage often utilizes precision operational amplifiers while maintaining signal integrity. A thorough design consideration in this stage is the control of common-mode signals and the enhancement of the signal-to-noise ratio (SNR). Moreover, careful layout and component selection are essential to prevent the interference of environmental noise sources [22]. Ultimately, the second amplifier stage serves as a bridge between the sensitive, high-impedance input front-end and the digital processing unit, ensuring that the analog signal is clean, amplified, and within the optimal voltage range for accurate conversion and analysis.

3.1.5. STM32F103C8T6 microcontroller

The main control chip of this system is the STM32F103C8T6 microcontroller, which belongs to the STM32 family. It is built on the ARM Cortex-M3 architecture. The processor has rich peripheral resources and runs fast up to 72 MHz, 3.3 V, with a typical 300 mA current consumption, which has low power characteristics, supporting the stable operation of the system. It has 64 KB of flash memory and 20 KB of SRAM for storing programs and data.

The STM32F103C8T6 microcontroller manages the ADC operations, applies initial data buffering, and handles the transfer of the acquired EEG data to the PC. An important aspect of this microcontroller is its power management features, which include low power consumption [23]. STM32CubeIDE is employed for the development and programming of the microcontroller, facilitating efficient data handling.

3.2. Method

The process of measuring and monitoring EEG signals is achieved through dry silver chloride electrodes strategically placed over the human scalp, according to the 10-20 international system, and the electrodes connect via unipolar methods. Each of the dry electrodes captures raw EEG data. The EEG acquisition signals are amplified in two stages and filtered side by side, then the signal is configured to match the input range of the STM32F103C8T6 microcontroller's 12-bit ADC. After processing, the data is transmitted via the USB connection to the personal computer (PC) for further processing and analysis, as shown in figure 3. The software environment utilizes MATLAB for advanced signal processing and data analysis, allowing for detailed examination of EEG rhythms.

A key contribution of this work is the custom-built MATLAB 2024 interface, which provides real-time signal monitoring and advanced spectral analysis through a GUI. The interface offers options for displaying raw EEG data and can be saved for analysis at any time. In addition, it facilitates applying Independent Component Analysis (ICA) for removing artifacts such as EOG and ECG. Also, feature extraction is provided by the software through computing PSD for each channel using brain waves such as alpha, beta, theta, and Gamma. Finally, using classification algorithms like the SVM to detect the emotional state.

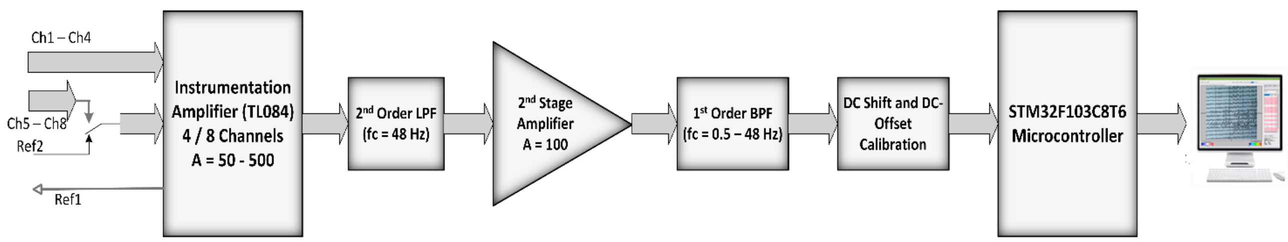


Figure 3. The Schematic Diagram of the Proposed System.

As shown in figure 3, when the wearable device part is in contact with the human's scalp and the hardware device, it will receive data continuously from the dry electrodes (AgCl) in the device. The steps for measuring EEG signals in a human with emotion detection can be explained as follows:

3.2.1. EEG acquisition signals

The EEG data is initially captured using dry electrodes. This data represents the brain activity measured in real-time. During EEG data collection, raw EEG data have various types of noise and artifacts, includes electrooculographic (EOG) resulting from blinking or eye movements occurring in the range 4 – 19 Hz, electromyographic (EMG) arise from muscle activity at frequencies above 25 Hz, electrocardiographic (ECG) due to heart contractions appearing at 1 Hz, and electrical power at 50 Hz.

The location of the electrodes in Fp1, Fp2, AF1, AF2, A1, and A2 in the earlobes is distributed according to the 10-20 international system.

The study is being conducted on four healthy participants (2 male and 2 female), aged between 20 and 40 years. All of them were familiar with the device's functioning, and emotions are stimulated using a series of standard videos from the International Affective Film System (IAFS), each of 4 minutes long and selected according to their emotional response (Arousal, valence) from the dataset DEAP [24].

The emotions are arranged as follows: boring, calm, fear, and happy. Also, each section is separated by a 2-minute break to avoid emotional overlap.

3.2.2. Instrument amplifier TL084

To achieve a high resolution of EEG signals, a multistage amplifier is utilized. The pre-amplifier is an instrument amplifier TL084, with high input impedance JFET inputs, low noise, and strong anti-interference ability. The instrument amplifier introduces initially amplifier gain from 50 to 5000 times, amplifying the weak amplitude EEG signals with a microvolt range to a millivolt range, while a high Common Mode Rejection (CMRR) is vital for eliminating external interferences. Typically, in this stage, the CMRR exceeding 100 dB

3.2.3. Low-pass filter

Utilizing a Low-pass filter with a 48 Hz cutoff frequency, to remove and eliminate noise and artifacts like the power line 50 Hz and muscle artifacts that appear above 48 Hz. According to the needs of the system, smooth roll-off characteristics are achieved using a Sallen-Key active filter. Which is preferred for simplicity and low-cost implementation.

3.2.4. 2nd amplifier

The EEG signal remains in the mV range; therefore, apply the second amplifier circuit with a gain of 100 times, which provides the EEG data result in a voltage range to achieve the design requirements. Finally, the overall gain of the system is about 5000-50000 times.

3.2.5. Band-pass filter

Design a band-pass filter with a cutoff frequency from 0.5 to 48 Hz to separate the EEG rhythms. In order to obtain a high signal-to-noise ratio and an Analog-to-Digital Converter with antialiasing.

3.2.6. Data conversion

In the STM32F103C8T6 microcontroller, data conversion via the 12-bit analog-to-digital (ADC) in this system requires configuring the ADC for the needs resolution and sampling rate. The analog voltage is converted to a digital format utilizing a resolution of 12 bits and a sampling rate of 500 Hz, with the outcome being digital data that is retained in a buffer for subsequent processing.

3.2.7. DC-Offset

Although the cutoff frequency is 0.5 Hz, the operational amplifier results in a DC offset that can be eliminated by using special DC circuits to attain a desirable EEG system with zero DC voltage drift.

3.2.8. Personal computer

After acquiring the EEG signals and completing the operations of the hardware system. The data is converted to a personal computer for display on MATLAB2024 with a GUI interface, which is shown in the EEG Reader application. It can monitor the EEG data and record it in a file (.mat) for further analysis and processing.

The EEG Reader demonstrates raw data for brain activity after amplification and filtering; the signals carry some artifacts, which can be removed by using Independent Component Analysis (ICA). ICA that distinguishes hybrid signals, including the High-Order statistical data characteristics [25]. It has effectively removed electrooculographic (EOG) and electromyographic (EMG). This approach maximizes the retention of relevant EEG information while effectively denoising the signal.

Independent Component Analysis (ICA) is employed to enhance the feature extraction performance of EEG Signals [26]. Components associated with eye activity (high amplitude from frontal electrodes and sudden appearance in the band (4-19) Hz), and muscle activity (>25 Hz) are removed based on spectral and topographic analysis in the section. This processing technique is significant, ensuring the minimization of artifacts. Balancing between computational complexity and the most effective method is critical for practical applications in EEG analysis.

After the ICA of the EEG signals is completed, extracting the features of these signals is necessary. Feature Extraction is more critical for improving emotion recognition accuracy, and selecting suitable parts guarantees for subsequent data processing.

In the step of feature extraction, it focuses on enhancing signal quality and extracting significant features, such as Frequency-domain analysis. It transforms EEG signals collected in the time domain to the frequency domain. These data are divided into rhythm signals. Then, we extracted all components of the rhythm signal by applying the Power Spectral Density (PSD), which estimates the original signal's power spectrum that varies with frequency.

This is achieved by the PSD related to EEG rhythms (delta, theta, alpha, beta, and gamma) for all channels. This can be employed as an essential method. The most common methods of PSD are classic spectrum estimation, which is reached by the Fourier transform (FT)[27]. Let the EEG signal represented be x(t), its autocorrelation function is r(k), PSD function P(w) is defined in Eq (1) [28],as:

$$P(w) = \sum_{k=-\infty}^{+\infty} r(k)\, e^{-i\omega k} \qquad (1)$$

Also, the most common method of classic spectrum estimation is the direct method, which achieves a periodic spectrum estimate by Eq (2) [29],

$$\hat{p}(w) = \frac{1}{N} \left| \sum_{t=1}^{N} x(t) e^{-i\omega t} \right|^2 \qquad (2)$$

Where N is the length of the signal. However, this method improves the accuracy of the power spectrum, but the variance is large, and can be improved by using PSD (Welch’s method), which reduces the fluctuation in spectrum estimates from compilation estimates from nested windows, and gives more stability. Sensitivity analysis confirmed that a 2-second Hanning window with 50% overlap maximized recognition performance [30].

After feature extraction that provides the enhancement accuracy classification, these features are transferred to the classifier to emphasize classification by applying a support vector machine (SVM). This can be used to draw the boundary between two or four emotion categories, and then label the category based on the features it selects. The boundary can be represented as a separate hyperplane belonging to a multidimensional feature space [31].

3.3. Support vector machine algorithm

Support vector machine (SVM) provides the benefits of training data in a higher-dimensional space to determine whether the hyperplane accurately recognizes the dataset while maximizing distances between each data point [32]. As illustrated in figure 4. This can be summarized as the fundamental principle of SVM, which maps the indivisible data to the high-dimensional data space, then finds a hyperplane that classifies data correctly and takes the distance from this plane to all data to the maximum [33].

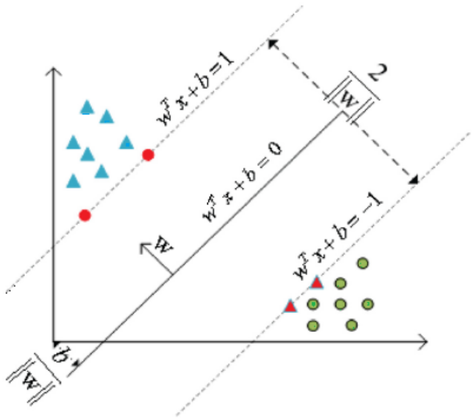


Figure 4. Fundamentals of Support Vector Machine [34].

4. Results and Discussion

Researchers used specific evoked emotion stimulation of brain cells to generate EEG signals that are spontaneous with corresponding characteristics. Therefore, this research uses a video to induce emotion in a person.

The system starts by distributing the electrodes over the human's scalp in locations (Fp1, Fp2, AF1, AF2, A1, and A2) to acquire the raw data. After processing the collected EEG signals through the hardware and then logging and analyzing the EEG data with MATLAB2024 through the EEG Reader application, as shown in Figure 5.

The GUI EEG Reader includes options that include initializing the configuration of the related serial port COM3, displaying raw EEG data, and saving it for analysis at a later time. Also, computing fast Fourier transforms (FFT) and analyzing the PSD for each channel using EEG rhythms, as demonstrated in figure 6. Regarding the evaluation of the device's accuracy specifically on persons, a closed-open eye test was applied. The device successfully generated a spike in the EEG signal, as depicted in figures 7 and 8.

After extracting the features that ensure the accuracy of emotion recognition, EEG features are subsequently recognized using a support vector machine. Utilizing evaluation metrics such as precision (positive predictive value), Recall(sensitivity), F1-score (harmonic mean between precision and recall), and specificity is essential for practically assessing the system performance. Table 2 provides the detection and analysis of emotion state, highlighting the adjustments between sensitivity and accuracy.

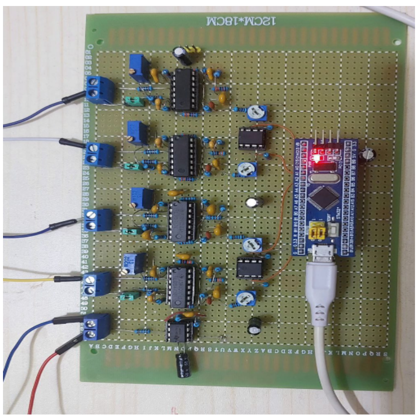


Figure 5. EEG Hardware Design.

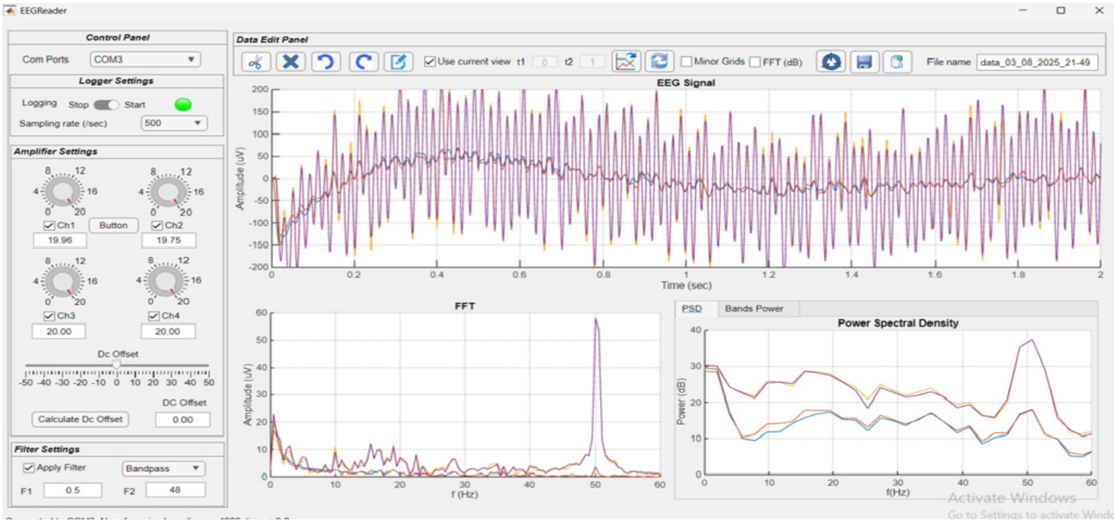


Figure 6. Interface EEG Reader.

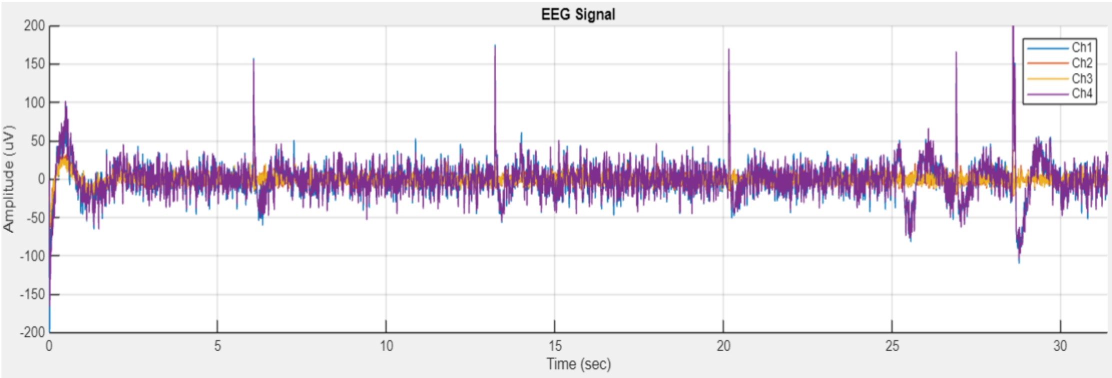
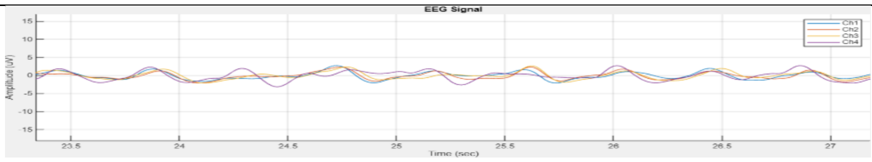
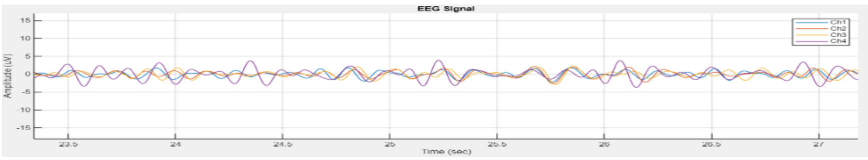


Figure 7. Open-Close Eye Test.

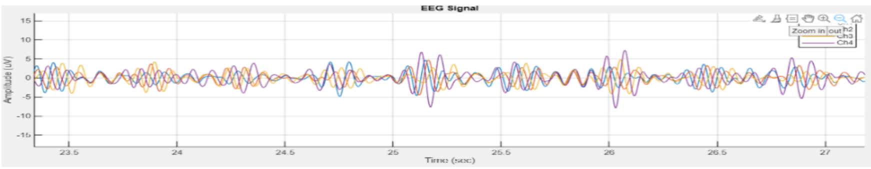
Delta waves (0.5-4) Hz



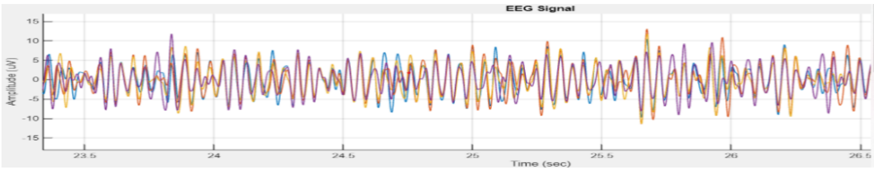
Theta waves (4-8) Hz



Alpha waves (8-13) Hz



Beta waves (13-30) Hz



Gamma waves (30-48) Hz

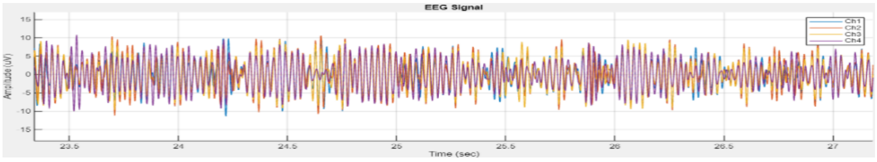


Figure 8. EEG Rhythms

Table 2. Emotion Detection Based on SVM Algorithms.

EMOTION	PRECISION	RECALL (SENSITIVITY)	F1-SCORE	SPECIFICITY
Boring	0.84	0.82	0.83	0.91
Calm	0.86	0.85	0.85	0.92
Fear	0.81	0.78	0.79	0.89
Happy	0.80	0.77	0.78	0.88

To further evaluate classification performance, a convolution matrix is constructed in Table 3.

Table 3. Confusion Matrix

		Predicted			
		B	C	F	H
True	B	0.82	0.08	0.06	0.04
	C	0.10	0.85	0.03	0.02
	F	0.05	0.07	0.78	0.10
	H	0.06	0.05	0.12	0.77

To assess the reliability of the proposed low-cost EEG system for emotion detection, statistical tests are performed on the classification results. A Chi-square test is conducted on the detection results of the four emotions (Boring, Calm, Fear, and Happy). The analysis revealed significant differences in classification ($x^2 \approx 9.6, p < 0.05$). Specifically, the system shows Calm is detecting more than Happy, while Boring and Fear have intermediate performance levels. This result reflects that the classifier performance is not uniform across all emotion classes, and the Calm emotions are more robustly detected.

Table 4. Comparison of The Proposed System with Other Systems

Ref /year	System	Stimuli	classifier	Accuracy%
Suhaimi et al. [7]/2022	Low-cost VR EEG system	VR video	SVM	85.0
Shilaskar et al. [10]/2023	Commercial-grade EEG device	Video	SVM	79.03
Attia et al. [11]/2024	Research-grade EEG device	EEG data	SVM	92.02
Mouazen et al. [12]/2024	DEAP dataset	Video clip	SVM+CNN	94-85
Proposed system /2025	Low-cost EEG system	Video	SVM	79-83

As shown in Table 4, the proposed system based on a cost-effective STM32F103C8T6 microcontroller achieves an accuracy of (79-83) %, which is comparable to recent studies that used high-priced and commercial-grade systems (Suhaimi et al.,2022; Attia et al.,2024). While deep learning approaches such as hybrid CNN-SVM achieve slightly higher accuracies of (85- 94) %, the system lies in its low-cost, wearable, and practical usability while maintaining competitive performance.

5. Conclusion

The presented paper explores the landscape of emotion in human cognition and interaction using a system, highlighting the significance through the utilization of low-cost components. This system provides a combination of dry electrodes, an instrument amplifier TL084, filtering, an STM32F103C8T6 microcontroller, and advanced signal processing tools in MATLAB 2024. The proposed system successfully detected primary emotion states such as boredom, calm, fear, and happiness. The achieved accuracy is from 79 % to 83 % using the support vector machine algorithm.

The significance of this EEG system lies in introducing a practical and reliable system for emotion detection, while being less expensive and less complex than traditional EEG devices. The statistical analysis confirms both accuracy and differential sensitivity of the system to specific emotional states.

The results enhanced the growing trend of using wearable, low-cost EEG devices for continuous brain activity monitoring, making emotion recognition technology more accessible for future diverse applications such as HCI, BCI, and medical fields.

Future work will include longitudinal studies with larger and more varied populations to evaluate the robustness and generalizability of the system over time.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Author Contributions

All authors contributed to formulating the research problem. Ghufran M. Fahad collected recent literature to establish the theoretical background of the study and proposed the implementation methodology. Riyadh A. Abbas was responsible for designing and assessing the accuracy of the methodology, while Manaf K. Hussein focused on validating the results and evaluating the reliability of the design. All authors participated in preparing the final version of this paper.

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